How do various maize crop models vary in their responses to climate change factors?

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Abstract

Potential consequences of climate change on crop production can be studied using mechanistic crop simulation models. While a broad variety of maize simulation models exist, it is not known whether different models diverge on grain yield responses to changes in climatic factors, or whether they agree in their general trends related to phenology, growth, and yield. With the goal of analyzing the sensitivity of simulated yields to changes in temperature and atmospheric carbon dioxide concentrations [CO_2], we present the largest maize crop model intercomparison to date, including 23 different models. These models were evaluated for four locations representing a wide range of maize production conditions in the world: Lusignan (France), Ames (USA), Rio Verde (Brazil) and Morogoro (Tanzania). While individual models differed considerably in absolute yield simulation at the four sites, an ensemble of a minimum number of models was able to simulate absolute yields accurately at the four sites even with low data for

calibration, thus suggesting that using an ensemble of models has merit. Temperature increase had strong negative influence on modeled yield response of roughly -0.5 Mg ha^{-1} per °C. Doubling [CO_2] from 360 to 720 μmol mol^{-1} increased grain yield by 7.5% on average across models and the sites. That would therefore make temperature the main factor altering maize yields at the end of this century. Furthermore, there was a large uncertainty in the yield response to [CO_2] among models. Model responses to temperature and [CO_2] did not differ whether models were simulated with low calibration information or, simulated with high level of calibration information.

Introduction

Maize is vital for the food security of many vulnerable populations (Bruinsma, 2009). It is also an important crop for its impact in the economy as a commodity. As any other crop, maize production is sensitive to climate, and climate is changing in ranges that are expected to alter maize crop efficiency (Adams *et al.*, 1998; FAO, 2012). It is therefore important that we understand how maize growth will be affected by changing climate factors. Given that future climate may be different in many maize cropping regions from what has ever been observed, especially as far as temperature and [CO_2] are concerned, process-based models are therefore essential tools to address that question.

Process-based crop models are widely used in climate change studies because they account for the response of physiological processes of crop growth and development to environmental and management variables, integrating complex and nonlinear effects of climate on crops (Tubiello & Ewert, 2002). They are also used to assess impacts and examine adaptation strategies of cropping systems to climate change (Adams *et al.*, 1990; Stöckle *et al.*, 1992; Rosenzweig & Wilbanks, 2010; Ewert *et al.*, 2011; White *et al.*, 2011), including plant breeding for climate change adaptation (Tao & Zhang, 2010; Boote *et al.*, 2011; Singh *et al.*, 2012). While there is broad agreement on the effects of elevated [CO_2] and temperature on crop growth and development, different researchers have packaged this knowledge in multiple simulation models that differ in their required input information, parameterization protocols, and methods to simulate the response of crop processes to the interaction of environmental and management factors. The various approaches and parameterization

that the models incorporate may lead to different simulated responses to climate change factors, which add uncertainty to the assessment of future world food supply and the identification of adaptation strategies (White *et al.*, 2011; Angulo *et al.*, 2013).

As objectives and purposes of models differ, model structure as well as model parameterization may result in different projected impacts of climate change, because physiological processes are variously formalized across models. A number of models might be equally good at representing the past but may respond quite differently in future conditions not experienced in current climate. For example, crop growth processes such as photosynthesis and respiration may show a non linear response when temperature increases and that may not be adequately represented in all models (Porter & Semenov, 2005). Given the impossibility of validating the response to future projections, a good assessment of the various uncertainties linked to the use of crop models in varying climatic conditions is required for deriving sound conclusions from model outputs (Tao *et al.*, 2009a,b; Rötter *et al.*, 2011). Consequently, assessing crop yield responses to future conditions based on an ensemble of possible outcomes from multiple simulation models may be more reliable than using one single model outcome that may not sufficiently capture all relevant processes (Tao *et al.*, 2009a, b). Studies to estimate the variability among crop models for response to climatic factors have already been explored for wheat and barley (Diekkrüger *et al.*, 1995; Goudriaan, 1996; Palosuo *et al.*, 2011; Rötter *et al.*, 2012; Asseng *et al.*, 2013), but similar studies are scarce for maize in spite of the great economic importance of that crop. Recently, a model intercomparison conducted for seven maize models in two contrasting years and two locations in Austria showed that models responded differently to heat and drought stress (Eitzinger *et al.*, 2013). Given the importance of maize worldwide, further investigation involving a wider range of environmental conditions over additional crop models is needed (Rosenzweig & Wilbanks, 2010). Though maize is a C_4 crop with a [CO_2] concentrating mechanism

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supportive of Rubisco function in the leaf bundle sheath (Kanai & Edwards, 1973), understanding the processes responsive to [CO_2] enrichment is important due to implications on photosynthesis, radiation use efficiency, water use, nutrient capture and use efficiency. The analysis of different CO_2-fixation algorithms within one model platform showed distinct differences in wheat yields with significant impacts of site conditions on the contribution of reduced transpiration (Kersebaum & Nendel, 2014). However, studies testing whether the [CO_2] relationships implemented in the models give consistent and accurate responses to [CO_2] across models are lacking (Boote *et al.*, 2010). Temperature affects many more processes in crop simulation models than does [CO_2] (Boote *et al.*, 2010), because temperature affects phenological development as well as growth and biomass partitioning. Thus, there may be higher variability among models for temperature response as compared to the variability induced by [CO_2].

A thorough assessment of the variation in the response of different models to climate change factors is critical to assess future maize production. Before projecting what the future yield may be under changed climate using a large number of models, it is critical to determine how much individual model simulations of responses to climate factors may vary. The objectives of the present work are to evaluate widely used maize crop models to (i) explore how maize crop models differ in simulations of yield, development, and water use in response to climate change factors [temperature and (CO_2)] in four contrasting pedo-climatic sites of maize production; (ii) provide a range of possible outcomes of crop growth and yield under varying levels of temperature and [CO_2]; (iii) quantify important sources of variation among crop model simulations such as phenology, primary production or harvest index; (iv) evaluate whether model response to climatic factors differs depending on the extent of the information available to calibrate the models for each region. The latter is important, considering that crop models are often used to simulate yields in regions where detailed model input information and/or reference data are seldom available.

This work is an initiative of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013), which links the climate, crop, and economic modeling communities to perform integrated climate impact assessments and improve the simulation of crop response to future climate change. Similar AgMIP studies have been performed using 27 wheat models (Asseng *et al.*, 2013) and 13 rice models. AgMIP pilots are also being organized for sugarcane, soybean, groundnut, potato, and sorghum/millet.

Materials and methods

Models

Twenty three maize models, accounting for the majority of maize models, were intercompared in a maize study as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al.*, 2013). Table 1 presents the major characteristics of the participating models, including a reference for each of them and with details on procedures used to simulate major processes (Palosuo *et al.*, 2011):

Phenology. Effects of life cycle drivers (temperature, photoperiod), and/or stresses (e.g., McMaster & Wilhelm, 1997).

Growth. Radiation use efficiency (Monteith, 1977), transpiration use efficiency (Tanner, 1981) or a leaf-level formulation of photosynthesis and respiration (Farquhar *et al.*, 1980; Von Caemmerer, 2000). Most of the models simulate leaf area dynamics dependent on crop phenological stage, following a canopy-level (e.g., Jones & Kiniry, 1986) or a leaf-level (e.g., Lizaso *et al.*, 2011) description.

Yield formation. Harvest index approach, dry matter allocation to the different organs, or grain number per unit of biomass approach.

Water dynamics. Simplified 'tipping bucket' capacity approach or a detailed Richards-type approach for infiltration and redistribution of water in the soil. For evapotranspiration, available methods varied and are indicated in Table 1. For transpiration, limitations of soil and plant water potential or soil water content are considered.

Nitrogen dynamics. Modules calculate soil and/or plant nitrogen balance.

Simulations of each model were run by scientists already experienced in the use of that particular model. Because most models do not account for the effect of pests, and because the impacts of climate on the biotic factors directly, were not considered here, this capability was disabled in all simulations. Four models have no CO_2 function (Sarra-H, Expert-ceres maize, Wofost, and Pegasus). The same input data were provided to each modeler (soil, weather series, crop management, see below for the details). All outputs were generated using the same protocol, and submitted to an agreed upon group of scientists that coordinated and centralized input and output processing.

Data for model evaluation

Sites and weather. Four sentinel sites representing important pedo-climatic zones of maize production were selected for model intercomparison. The four sites were: Lusignan, France (46.25°N; 00.07°E; 150 m elevation); Ames, Iowa, USA (42.01°N; 93.45°W; 329 m elevation); Rio Verde, Brazil (17.52°S; 51.43°W; 731 m elevation), and Morogoro, Tanzania

Table 1 Modeling approaches of the models involved in the study. Some of the descriptions are reported as in Palosuo et al. (2011). References: APSIM-maize (AM); Keating et al. (2003); CropSyst (CS); Stöckle et al. (2003); DSSAT-CERES maize (DC); Jones & Kiniry (1986); EPIC maize (EM); Williams et al. (1989); Expert-N - CERES - Maize (NC) Expert-N - SPASS - Maize (NP); Expert-N - SUCROS-Maize (NS); Stenger et al. (1999); HERMES (HE); Kersebaum (2007); HYBRID-maize (HY); Yang et al. (2004); InfoCrop (IN); Aggarwal et al. (2006); IXIM (IX); Lizaso et al. (2011); LINPAC (LC); Jing et al. (2012); LPJml (LP); Bondeau et al. (2007); MAIZSIM (SM); Kim et al. (2012); MCWLA (MC); Tao et al. (2009a,b); MONICA (MO); Nendel et al.(2011); MSB (MS); Muchow et al. (1990); PEGASUS (PE); Deryng et al. (2011); PlantSys 1.0 (PS); Jongschaap (2007); SALUS (SA); Basso et al. (2010); SARRAH (SH); Baron et al. (2005); STICS (ST); Brisson et al. (2003); WOFOST (WO); Boogaard et al. (1998)

Model (2-letter code)	Leaf area development and light interception[a]	Light utilization[b]	Yield formation[c]	Crop phenology[d]	Root distribution over depth[e]	Stresses involved[f]	Type of water stress[h]	Type of heat stress[j]	Water dynamics[i]	Evapotranspiration[n]	Soil CN-model[p]	CO2 effects[q]	Number of cultivar coefficients	Climate input variables[r]	Model relative[s]	Model type[r]
APSIM-maize (AM)	S	RUE TE	Prt	T DL	EXP	W A H	S	V	C	PT	CN P (3) B	RUE TE	5	R Tx Tn Rd	C	P
CropSyst (CS)	I	RUE TE	HI B Prt (post anthesis)	T DL	EXP	W N H	E	V R	C	PM	CN P (1)	TE RUE T	13 (+)	R Tx Tn Td Rd W	CR S	P
DSSAT-CERES maize (DC)	S	RUE	Gn	T DL	EXP	W N A	E	–	C	PM	CN P (4) B	RUE TE	6	R Tx Tn Rd	–	P
EPIC maize (EM)	S	RUE	HI B	T DL	EXP	W N O	ET S	E D	C	PM	CN P (5)	RUE TE	57	Rd Tx Tn RH W	C G	P G
Expert-N - CERES - Maize (NC)	S	RUE	B Gn	T DL	EXP	W N H	E S	V	R	PM	CN P (3) B	–	6	R Tx Tn Rd RH W	C	P

Table 1 (continued)

Model (2-letter code)	Leaf area development and light interception[a]	Light utilization[b]	Yield formation[c]	Crop phenology[d]	Root distribution over depth[e]	Stresses involved[f]	Type of water stress[h]	Type of heat stress[i]	Water dynamics[j]	Evapotranspiration[n]	Soil CN-model[p]	CO_2 effects[q]	Number of cultivar coefficients	Climate input variables[r]	Model relative[s]	Model type[t]
Expert-N - SPASS - Maize (NP)	D	P-R	Prt	T DL	EXP	W N H	E S	V	R	PM	CN P(3) B	RUE	8	R Tx Tn Rd RH W	C S	P
Expert-N - SUCROS - Maize (NS)	D	P-R	Prt	T	EXP	W N H	E S	V	R	PM	CN P(3) B	RUE	3	R Tx Tn Rd RH W	S	P
HERMES (HE)	D	P-R	Prt	T DL O	EXP	W N A	E S	–	C	PM	N P(2)	RUE TE	6	R Tx Tn Rd e RH W	S C	P
HYBRID-maize (HY)	S	P-R	Gn	T	EXP	W	E	–	C	PM	–	–	1	R Tx Tn Rd e RH W	C L	P
InfoCrop (IN)	D	RUE	B Gn Prt	T DL	EXP	W N[g] T	E	V R	C	PM	CN	TE RUE	10	R Tx Tn Rd e W	S OW M	P

Table 1 (continued)

Model (2-letter code)	Leaf area development and light interception[a]	Light utilization[b]	Yield formation[c]	Crop phenology[d]	Root distribution over depth[e]	Stresses involved[f]	Type of water stress[h]	Type of heat stress[i]	Water dynamics[j]	Evapotranspiration[n]	Soil CN-model[p]	CO_2 effects[q]	Number of cultivar coefficients	Climate input variables[r]	Model relative[s]	Model type[t]
IXIM (IX)	D	P-R	Gn	T, DL	EXP	W, N, A	E	–	C	PM	CN, P (4), B	RUE, TE	8	R, Tx, Tn, Rd	C	P
LINPAC (LC)	I	RUE	B, Prt	T	NON	W, N[g], H	E	V	C	PM	–	RUE, TE	10	R,Cl, Ta, Rd, E, W	U	G
LPJml (LP)	S	P-R	HI, B	T	LIN	W	E	–	C[m]	PT	–	F	3	R, Ta, Sun/Cld	E	G
MAIZSIM (SM)	D	P-R	Prt	T, DL, O	CD	W, N, A, H	S	V, R	R	P –Energy balance	N, P (1), B	LF, QE, TE, GY	2	R, Tx, Tn, Rd, Rh, W	CS	P
MCWLA (MC)	S	P-R	HI, B	T	EXP	W, T, H	E	V R	R	PM	–	PT	7	R, Tx, Tn, Rd, e, W, Daily/hourly	–	G
MONICA (MO)	D	P-R	Prt	T, DL, O	EXP	W, N, A, H	E, S	V	C	PM	CN, P (6), B	PT, F	6	R, Tx, Tn, Rd, RH, W	H	P

Table 1 (continued)

Model (2-letter code)	Leaf area development and light interception[a]	Light utilization[b]	Yield formation[c]	Crop phenology[d]	Root distribution over depth[e]	Stresses involved[f]	Type of water stress[h]	Type of heat stress[i]	Water dynamics[j]	Evapotranspiration[n]	Soil CN-model[p]	CO_2 effects[q]	Number of cultivar coefficients	Climate input variables[r]	Model relative[s]	Model type[t]
MSB (MS)	I	RUE	Prt	T	NON	W N	S		C	PT	CN		17	R Tx Tn Rd		P
PEGASUS (PE)	S	RUE	B Prt	T	NON	W Nu H	E S	V	C^m	PT	C P (1)	–	1	R Ta Sun/Cld	E	G
PlantSys 1.0 (PS)	D	P-R	Prt	T DL O	CD	W N H	E S	VR	C	P	CN P(3) B	LF	43	R Tx Tn Rd(sun) E W	S	P
SALUS (SA)	S	RUE	Prt HI	T DL	EXP	W N H	E	V	C	PT	CN P (3) B (2)	RUE TE	18	R Tx Tn Rd	C	P
SARRAH (SH)	S	RUE	HI Prt	T	LIN	W	S	–	C	PM	–	–	6	R Rd or Ins Tx Tn ETo	C	P
STICS (ST)	D	RUE	HI (Gn) B	T DL O	SIG	W N H	S	V R	C	PT	CN P (3) B	RUE	15	R Tx Tn Rd e W	C	P

Table 1 (continued)

Model (2-letter code)	Leaf area development and light interception[a]	Light utilization[b]	Yield formation[c]	Crop phenology[d]	Root distribution over depth[e]	Stresses involved[f]	Type of water stress[h]	Type of heat stress[i]	Water dynamics[l]	Evapotranspiration[n]	Soil CN-model[p]	CO_2 effects[q]	Number of cultivar coefficients	Climate input variables[r]	Model relative[s]	Model type[t]
WOFOST (WO)	D	P-R	Prt B	T DL	LIN	W A N[g]	S	V	C[m]	P	–	–	6	R Tx Tn Rd e W	L	PG

[a]Leaf area development and light interception; Simple-unilayer (=S) or Detailed-multilayer (=D) approach; I = intermediate.

[b]Light utilization or biomass growth: RUE = Simple (descriptive) Radiation use efficiency approach, P-R = Gross photosynthesis–respiration, TE = compute water use first, then biomass growth from transpiration efficiency.

[c]Yield formation depending on: HI = fixed harvest index, B = total (above-ground) biomass, Gn = number of grains and grain-growth rate, Prt = partitioning during reproductive stages.

[d]Crop phenology is a function of: T = temperature, DL = photoperiod (day length); O = other water/nutrient stress effects considered.

[e]Root distribution over depth: linear (LIN), exponential (EXP), sigmoidal (SIG), no roots-just soil depth zone (NON), CD = Convective Dispersive.

[f]Stresses involved: W = water stress, N = nitrogen stress, A = oxygen stress, H = heat stress; O = others (e.g., EPIC model considers stresses for both aboveground and below-ground growth. For Aboveground: water, temperature, nitrogen, phosphorus, potassium. For Belowground: bulk density (soil strength), aluminum tolerance (soil acidity), salinity, temperature (for root growth), and soil aeration).

[g]Nitrogen-limited yields can be calculated for given soil Nitrogen supply and N fertilizer applied.

[h]E = Eta/Etp, S = soil available water in root zone.

[i]V = vegetative (source), R = reproductive organ (sink).

[l]Water dynamics approach: C = 'Tipping bucket' capacity approach, R = Richards approach.

[m]Only two soil layers (top- and subsoil) are distinguished.

[n]Method to calculate evapotranspiration: P = Penman; PM = Penman-Monteith, PT=Priestley–Taylor.

[p]Soil C-N model (CN), N = N model, P(x) = x number of organic matter pools, B = microbial biomass pool.

[q]Elevated CO_2 effects on: LF = Leaf-level photosynthesis-rubisco or on QE and Amax; RUE = Radiation use efficiency, TE = Transpiration efficiency, PT = Photosynthesis and transpiration, F = Farquhar model, GY = Grain Yield; T = Stomatal conductance.

[r]R = rainfall, Tx = Tmax, Tn = Tmin, Ta = Taverage, Td = dewpoint temperature, Rd = radiation, e = vapor pressure, RH = relative humidity, W = wind speed, Sun = Fraction of sunshine hours, Cld = Fraction of cloud cover, ETo = potential evapotranspiration.

[s]C = CERES, L = WOFOST, H = HERMES, CS = CSGCL models (GOSSYM, GLYCIM, SPUDSIM), E = EPIC, S = SUCROS, CRS = CropSyst, U = LINTUL.

[t]P = point model (site-specific), G = global or regional model (regarding the main purpose of model).

(06.50°S; 37.39°E; 500 m elevation). Basic characteristics of the study sites are summarized in Table 2.

According to the FAO classification, the soils are Cambisol in Lusignan, Gleysol in Ames, Geri-Gibbsic Ferralsol in Rio Verde, and Haplic Arenosol in Morogoro. Daily solar radiation, maximum and minimum air temperature (2 m), and precipitation for the 1980–2010 historical baseline climates were provided to crop modeling groups for all sites. Available daily measurements of surface wind speed, air humidity (dew point temperature, vapor pressure, and relative humidity at the time of day of maximum temperatures) were provided. Where these variables were not measured, they were estimated from the NASA Modern Era Retrospective-Analysis for Research and Applications (MERRA; Rienecker et al., 2011).

At Lusignan, France, the mean annual rainfall (1980–2010) is 819 mm, of which 28% falls between May and August. Ames, USA has a continental climate with temperature extremes of both hot and cold, and long-term mean annual precipitation (1980–2010) of 886 mm, 54% of which falls from May through August. Rio Verde, Brazil is the wettest location with a seasonal distribution of precipitation. The mean annual rainfall (1980–2010) is 1645 mm, with the rainy season extending from October through April. Morogoro, Tanzania is the warmest location with monthly mean maximum and minimum temperatures varying between 35 and 14 °C and long-term annual rainfall of 828 mm, with 90% falling from November through May.

Management. A one-year experiment at each location formed the basis of the comparison of observed and modeled data for the four locations. The field experiments were carried out from May to October in 1996 in Lusignan, from May to September in 2010 in Ames, from November to February in 2003–2004 in Rio Verde, and from November to January in 2009–2010 in Morogoro. Experiments were conducted according to the local practices for each region (Table 3). Lusignan and Morogoro were the two irrigated sites. Nitrogen fertilizer was not applied in Rio Verde because sufficient N was released by organic matter mineralization.

Crop measurements. Measured crop data for each site consisted of phenology (emergence, flowering, and maturity dates) and intensive in-season time-series information [soil water content, leaf area index (LAI), crop biomass] as well as end-of-season yield components. Details on the experiments are reported for Lusignan, France (Tayot *et al.*,1999; Brisson *et al.*, 2002), Ames, USA (Bortolon L & Hatfield JL, unpublished data), Rio Verde, Brazil (Maltas *et al.*, 2007, 2009), and Morogoro, Tanzania (Bobert J, Festo R, Kersebaum KC, Kashaigili JJ, Tumbo S & Mahoo H, unpublished data).

Low level calibration simulation procedures. In regional studies, many inputs required by crop models are often not available. To examine the effect of the level of detail in the input information upon the model response to climatic factors, we provided two levels of calibration information, a low (L) and a high (H) level. For level L, only soil, management inputs, and crop phenology data were provided. Models were run with standard soil initial conditions such as prior crop residue type depending on the previous crop (legumes or cereals)

Table 2 Characteristics of the sentinel sites. Site, latitude and longitude (Lat, Long), mean seasonal precipitation (P) and mean seasonal temperature (T) for the period 1980–2010, soil type (FAO classification), lower limit of soil water (LL), drained upper limit (DUL), bulk density (BD), rooting depth (Root D)

Site	Lat; Long	P[a] (mm)	T (°C)	Soil Type	LL (% v/v)	DUL (% v/v)	BD (g cm^{-3})	Root D (cm)
France	46.25°N; 00.07°E	378	17	Cambisol	15	32	1.13	120
Iowa	42.01°N; 93.45°W	476	21	Gleysols	14	34	1.38	200
Brazil	17.52°S; 51.43°W	980	25	Geri-Gibbsic Ferralsol	20	29	1.19	140
Tanzania	06.50°S; 37.39°E	258	27	Haplic Arenosol	35	51	1.22	130

[a]Precipitation and temperature refer to the growing season of each sentinel site, i.e. to May–October, May–September, November–February, November–January for the four locations, respectively.

Table 3 Sowing date, crop variety, plant density, total nitrogen (N) fertilization, total irrigation, prior crop residue type for the four sentinel sites selected for the simulation experiments. Details on the experiments are reported for France as in (Tayot *et al.*,1999; Brisson *et al.*, 2002), USA (Bortolon L & Hatfield JL, unpublished data), Brazil (Maltas *et al.*, 2007, 2009), and Tanzania (Bobert J, Festo R, Kersebaum KC, Kashaigili JJ, Tumbo S & Mahoo H, unpublished data)

Site	Sowing date	Hybrid	Plant density (plant m^{-2})	Total N fertilizer (kg N ha^{-1})	Irrigation (mm)	Residue type
France	April 26	Furio	9.5	255	377	Maize
Iowa	May 4	Golden Harvest GH-9014	7.5	167	0	Soybean
Brazil	October 22	Pioneer 30K75	6.6	0	0	Fallow
Tanzania	October 26	TMV 1	9.5	61	178	Cassava/fallow

and using the soil organic carbon of the prevailing soil type of the region. The initial soil water content was set at field capacity (Lusignan, Ames) or wilting point (Rio Verde, Morogoro,) according to the general rainfall pattern of each location. Crop field management (sowing date and depth, plant density, nitrogen fertilization dates and amounts, irrigation schedule when applied), per-layer soil characteristics (wilting point, field capacity, saturation, bulk density, pH, and organic carbon and nitrogen), and local maximum observed rooting depth were also provided. Thus, simulations at level L were run at each site [for a single year (calibration) and for a 30-year-baseline and sensitivity tests (as described below)] using only the above described input information, with no parameter adjustment other than setting the time to anthesis and time to maturity observed in each region.

High level calibration simulation procedures. After the L level input simulations were completed, additional crop and soil information (H level) was supplied to each modeling group. The complete information provided included the actual soil initial conditions (water, nitrate, ammonium), and time series of above-ground biomass, LAI, soil water and nitrogen contents, and plant nitrogen. Soil and plant N information were not available for the Tanzania site. It was requested that each modeling group adjust model parameters (especially those depending on the cultivar) to improve the simulations based on the observed data, using whatever techniques they normally use and documenting the changes. For that purpose, each modeler was requested to send a report on changes made in the values of parameters and what logic was followed. Twenty-one groups completed the full assessment of that step. For the L simulation, modelers adjusted cultivar parameters of their previously simulated hybrids, to match the provided phenology. In the H simulation phase, finer adjustment of phenology and plant traits such as final leaf length, leaf number, specific leaf area (SLA) were made, if applicable. Modelers never changed parameters linked to photosynthesis or RUE, or any other temperature-sensitive relationships. Soil parameters (relationships of soil water potential and conductivity to soil water content) were also adjusted to match the initial conditions. Some simpler models designed for larger scales had less flexibility and were largely unaltered, except for phenology. The given cultivar was different at each site, so the cultivar parameter sets differed by site. Consequently, the adjustments for the H phase were larger because the models had never been used before at those sites. After parameters were adjusted, the models were run with the specific single year experiment at each site.

Climatic sensitivity analyses using modified 30-year climate series

To study simulated responses to climate change factors temperature and $[CO_2]$, models with parameters adjusted using H input level information were run for a 30-year-baseline and several modified 30-year weather files for the four locations.

The baseline weather series were modified by changing daily maximum and minimum temperatures (-3, 0, $+3$, $+6$

and $+9$ °C). Modeled responses were also compared under different levels of $[CO_2]$ (360, 450, 540, 630 and 720 μmol mol^{-1}). The temperature and $[CO_2]$ modifications were considered both in single factor series and in several combinations for the High input calibration simulations. As summarized in Table 4, simulations for the Low input case were limited to only the single factor variation in temperature and $[CO_2]$, with the goal of understanding how calibration influenced model sensitivity to temperature and $[CO_2]$. Simulated model response to $[CO_2]$ is presented only for the 15 models describing explicitly $[CO_2]$ effects, out of the models that concluded the High inputs simulations.

Simulation protocol

Simulation experiments were carried out for the 1980–2009 time series (30 planting seasons) for the baseline and the various modified 30-year weather data sets for the four locations. For each year, initial soil conditions were reset to those used for level L or for level H. The LPJmL model was run continuously with a 100-year spin up just to set the initial organic matter compartments of soils at each site. After this goal was achieved, it was run as the other models. Resetting the soil initial conditions eliminated any carry-over of water, nitrogen, or a change in soil organic matter. For the irrigated locations (Lusignan, France, and Morogoro, Tanzania), automatic irrigation was triggered when the soil water content within the top 50 cm depth dropped under 60% of the plant available water.

Analysis of model responses to temperature and $[CO_2]$

Comparative effects of single weather variables and interactions on model results (H information level averages over 30-year initial or modified baseline simulated yield, biomass

Table 4 Levels of CO_2 and temperature factors simulated for each location for the low and high input information simulations. Temperature factor levels applied to maximum and minimum daily temperatures of the 30-year-baseline weather data

Low level input	High level input
360 ppm -3 °C	360 ppm -3 °C
360 ppm 0 °C	360 ppm 0 °C
360 ppm $+3$ °C	360 ppm $+3$ °C
360 ppm $+6$ °C	360 ppm $+6$ °C
360 ppm $+9$ °C	360 ppm $+9$ °C
450 ppm 0 °C	450 ppm 0 °C
540 ppm 0 °C	540 ppm 0 °C
630 ppm 0 °C	630 ppm 0 °C
720 ppm 0 °C	720 ppm 0 °C
	540 ppm $+3$ °C
	540 ppm $+6$ °C
	540 ppm $+9$ °C
	720 ppm $+3$ °C
	720 ppm $+6$ °C
	720 ppm $+9$ °C

and transpiration) were evaluated with Analysis of Variance for each site. For that analysis, three levels of [CO_2], four temperature variations above the baseline, and models were considered fixed effects with 2, 3, and 18 degrees of freedoms, respectively. All interactions were tested. Climate factors and model effects were highly significant at all sites. So were interactions between temperature and CO_2 except in Lusignan ($P < 0.08$). Graphical analyses were also used for model inter-comparison by plotting medians and variability distributions (box-plots) of simulated outputs and used to estimate the responses of yield to T and CO_2.

Results

Importance of using calibrated results for studying the impact of climate change factors on maize yields

The results of ensemble simulations of yields at the four selected sites of this work were compared when minimal information (L) vs. high information (H, full initial conditions and experimental results) were provided to calibrate the models. Figure 1 illustrates the simulated yields of the one year experiments at each site with the L and H calibration information, representing before and after adjusting model parameters on the basis of observed crop and soil data. The ensemble of models simulated site-specific yield better than any given individual model, both at L and H levels. For each site, simulated yield with L calibration information averaged over the 23 models matched the observed data well within the experimental error, but with high variability among crop models. Hence, when the level of input information increased (High information calibration,

Fig. 1b), only the variability among models was strongly reduced.

To further investigate the value of using a minimum number of models to assess the yield with low information, a simulation of ensemble modeling using n models was made (Fig. 2). Groups of n different models were randomly created among the total combination of non repeated groups of n models. Care was taken to form groups from different models only and that each group of n was not repeated. Starting with groups of two models until groups of 21 models, 210 groups were chosen randomly among all possibilities (21!/(21 − n)!/n! all together) for each set of n models. In sites where fewer than 21 modelers achieved all simulations, the maximum number of models per set tested was 19. Then the absolute value of the difference between the experimental yield and the average yield of each ensemble of n models simulations was computed. Finally, the mean and standard deviation of these 210 differences was computed and related to the experimental yield to provide an estimate of relative variation. At each site, the relative variation declined as a function of n (Fig 2) and so did the standard deviation of the 210 absolute differences (data not shown). The relative variation depended on the site. Morogoro exhibited the largest variation followed by Rio Verde, Lusignan, and Ames.

Temperature responses

Yield. At all four sites, the median of simulated maize grain yield highly significantly decreased with
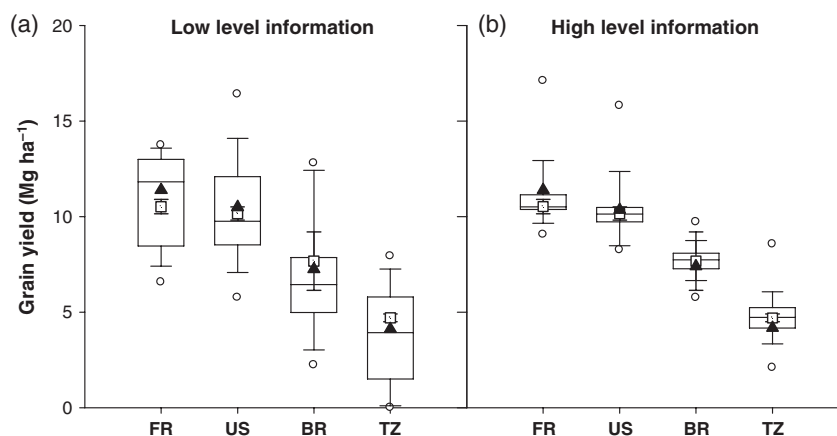

Fig. 1 Observed and simulated one year maize grain yield (Mg ha^{-1}) for four locations using 17 maize simulation models and two levels of input information: (a) Low level (anthesis and maturity dates, soil data with generic initial conditions, management); (b) High level (in addition to low level, observed soil initial conditions, time course of leaf area, biomass, yield, soil water content, soil, and crop N). Locations were: Lusignan, France (FR), Ames, Iowa, USA (US), Rio Verde, Brazil (BR), and Morogoro, Tanzania (TZ). Open squares are mean observed grain yields plus or minus one standard deviation. Filled triangles are the mean of simulated yields for each location. Boxes are delimiting the 25 and 75 percentile with the median inside. Whiskers are 10 and 90 percentile. Hollow circles indicate outliers.
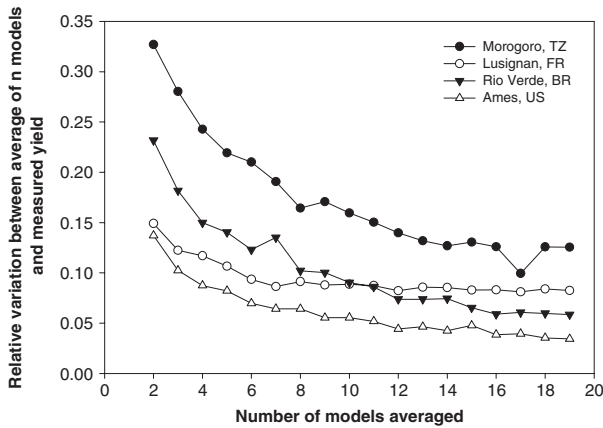
Fig. 2 Relative variation between observed and average yield simulated with n randomly selected models among 19 at 4 world sites, as a function of n. Each set of n models was composed with the requirement that each model of the set was used only once in a given set, and that all models were equally represented in the 210 sets.

temperature increase above current temperature levels (Fig. 3). The decrease in yield with an increase in temperature from 0 to +9 °C across 19 crop models was approximately linear and the median of models decreased from 9.8 to 6.3 Mg ha^{-1} at Lusignan (France), from 9.4 to 4.3 Mg ha^{-1} at Ames (USA), from 7.5 to 2.4 Mg ha^{-1} at Rio Verde (Brazil), and from 5.2 to 1.8 Mg ha^{-1} at Morogoro (Tanzania). This corresponded to a relative yield change of −4.5, −6.0, −7.8 and −7.1% per °C at the four sites, respectively. With only few exceptions, the 19 maize models with High inputs simulations generally agreed on a decline in yield with warmer weather. The models varied in magnitude of yield reduction with temperature increase, with 50% of models having sensitivity between −3.5% and −5.2% per °C in Lusignan, −4.8% and −6.6% per °C in Ames, −6.4% and −8.3% per °C in Rio Verde, and −3.4% and −9.8% per °C in Morogoro. The other models outside of this 50% had a lower or higher response ranging from no response up to double response with respect to
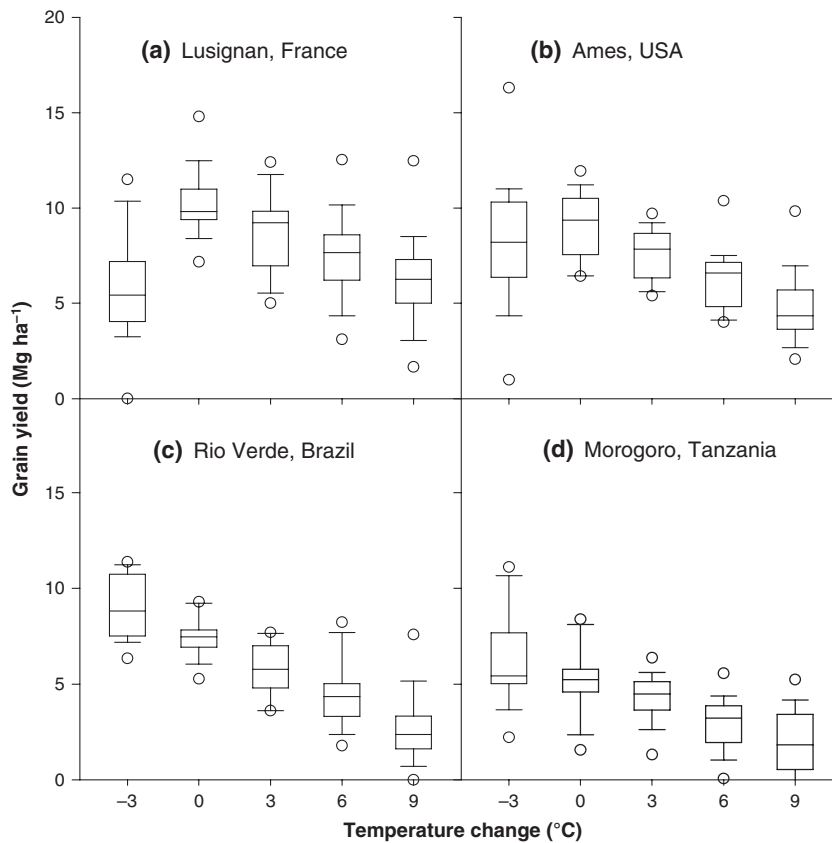
Fig. 3 Temperature effect on 30-year grain yield (Mg ha^{-1}) simulated by 19 models at Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d). Maximum and minimum temperatures were decreased every day by 3 °C, or increased by 0, 3, 6, and 9 °C. Box-plot description is similar to Fig. 1 except for the absence of measured and mean values. Mean baseline temperatures during the growing cycle were 17, 21, 25, and 27 °C in Lusignan, Ames, Rio Verde, and Morogoro, respectively.

the median relative yield change. The variation among absolute yield simulations as shown by the box-and-whisker plot was scarcely different as temperature increased.

However, at the cooler sites (Lusignan and Ames, the high-latitude sites), a lower temperature (−3 °C below baseline) resulted in lower simulated grain yield, probably because simulated biomass production rates decreased in the models, and crop maturity was prolonged and abruptly ended in the fall. At the warmer locations (the low-latitude sites), the 3 °C cooler temperature increased simulated yields (by 6.0% and 1.2% per °C in Rio Verde and Morogoro, respectively), suggesting that these sites are already warmer than the optimal growing climate (See Figures S1 and S2 in supplemental material for individual crop models response as a function of the 30-year seasonal temperature). The variability in responses among models increased with the −3 °C temperature scenario, especially at cool locations (Figure S2 in supplemental).

Phenology: the growth cycle shortens as temperature increases. The time from sowing to anthesis and time to maturity defines the opportunity of the crop to capture radiation and other resources, and was evaluated here as potential contributor to the yield response (Fig. 4). The time to anthesis was reduced as the temperature increased at all locations, with larger reductions in the cooler sites (Table 2). As temperatures were increased by 0 to +3 °C, the time to anthesis decreased on average of −5.5, −3.1, −2.4, and −1.5 days per °C for Lusignan, Ames, Rio Verde, and Morogoro, respectively. The impact of further temperature increase gave a higher response in the cooler sites. The variability in simulated responses among crop models was relatively small (See Figure S3 in supplemental materials for individual crop model responses to temperature), because phenology in these models is mostly driven by temperature using a mostly common growing degree day approach. Variability was usually larger at either high or low temperature scenarios. Time to crop maturity (Fig. 4) was also reduced with rising temperature at all sites, and that reduction was less pronounced at the warmer sites. The variability between crop models was larger for maturity date than for anthesis (Figure S4). The increased variability at the cooler sites (Lusignan and Ames) was related to the occurrence of cold temperatures at the end of the season. For Lusignan, France, in four models the crop failed to reach maturity across all the 30-year simulations when temperature decreased by −3 °C. In several models, the simulated crop extended its life cycle at the highest temperature in Morogoro, Tanzania, with crop failure to reach anthesis and maturity in one case.
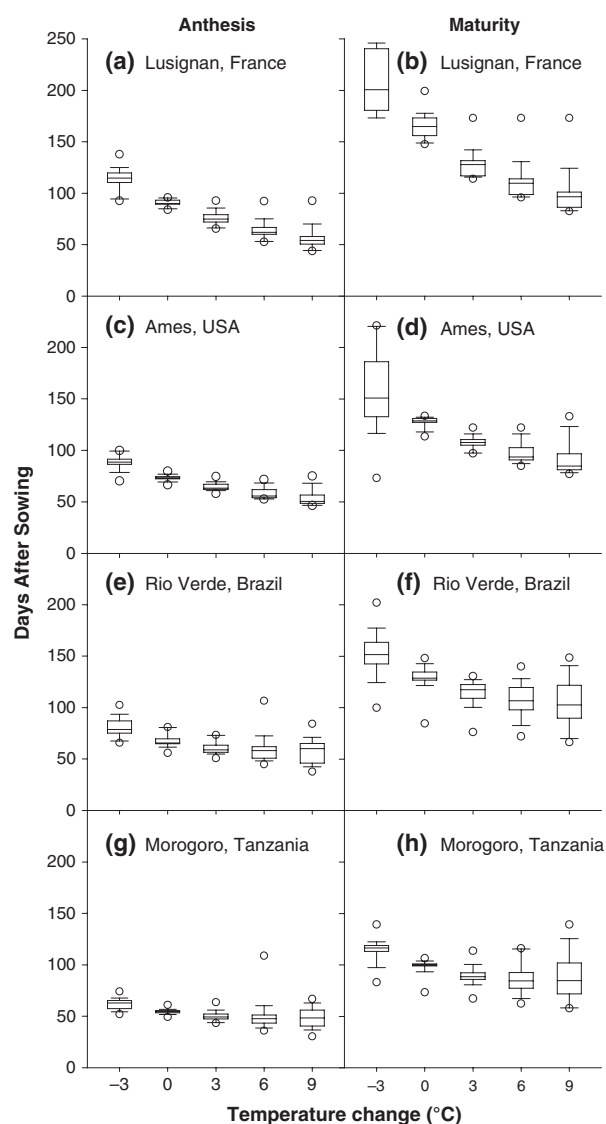

Fig. 4 Temperature effect on 30-year phenology simulated by 18 models at Lusignan (France), Ames (USA), Rio Verde (Brazil), and Morogoro (Tanzania). Phenology was expressed in days to anthesis (a, c, e, g), and days to maturity (b, d, f, h). Four models of 18 could not simulate maturity date in Lusignan, France with a decrease in temperature of −3 °C. One model could not simulate flowering and maturity dates in Brazil and Tanzania with an increase in temperature of +9 °C. Box-plot description is similar to Fig. 1 except for the absence of measured and mean values. Mean baseline temperatures during the growing cycle were 17, 21, 25, and 27 °C in Lusignan, Ames, Rio Verde, and Morogoro, respectively.

[CO₂] responses

Yield. The increase in [CO₂] resulted in a highly significant simulated increase in maize yield at all sites (Fig. 5). When [CO₂] was doubled, the increase in the median yield of the 15 models was 6.4%, 12.4%, 7.8%,

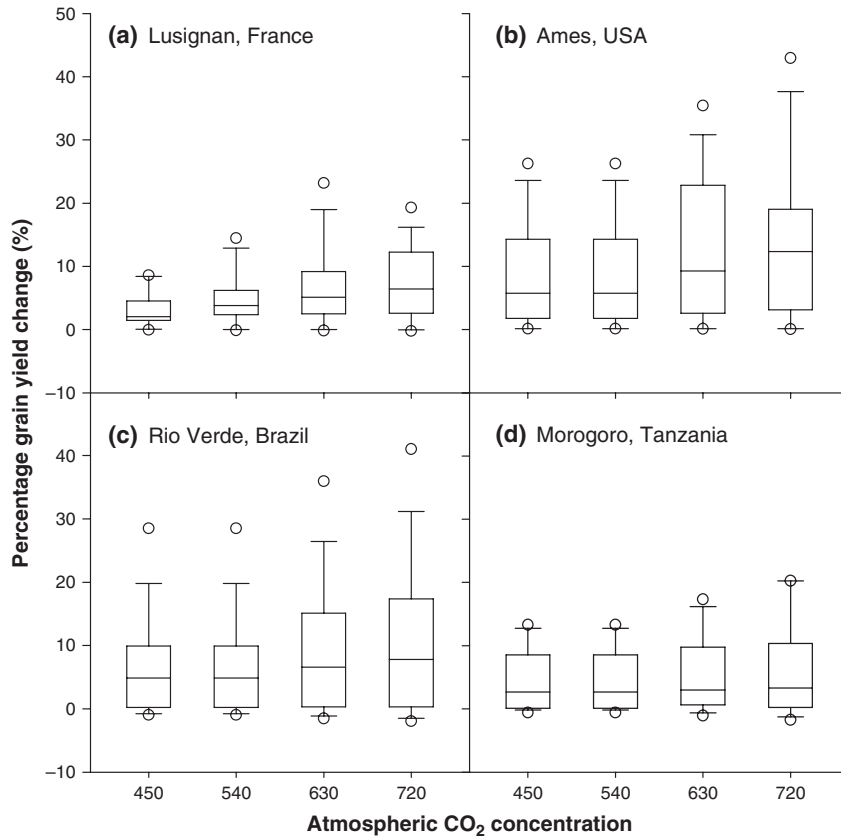**Fig. 5** Response of grain yield (%) to $[CO_2]$ for a 30-year time-series simulated by 15 models at Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d). Box-plot description is similar to Fig. 1 except for the absence of measured and mean values.

and 3.3% in Lusignan, Ames, Rio Verde, and Morogoro, respectively. Models varied considerably in their response to $[CO_2]$, with the 50-percentile ranging from no response to 19% increase at doubled $[CO_2]$ (See responses of individual models in supplemental materials, Figure S5). Considering the response of the median of all 15 models, the simulated yield increase from 360 to 720 μmol mol^{-1} was approximately continuous and close to 0.02% and 0.01% per μmol mol^{-1} in Lusignan and Morogoro. The variation among models was larger as the $[CO_2]$ level increased from current concentrations to 720 μmol mol^{-1}.

Crop transpiration. Seasonal crop transpiration was highly significantly reduced with increasing $[CO_2]$ with models varying considerably in the simulated total transpiration and in their response to $[CO_2]$ (Fig. 6 and Figure S6 in supplemental material.) On average, the models showed a steady decrease in transpiration with slopes of −0.015%, −0.009%, −0.008%, and −0.011% per μmol mol^{-1} in Lusignan, Ames, Rio Verde, and Morogoro. The variation among models was larger the larger the increase in $[CO_2]$.

Interannual variability in yields

Interannual variability was computed for each model at each location and expressed as CV (fraction) over the 30-simulated years. When the average of these CVs across the 19 models for each location were considered, the irrigated locations showed the lowest average values of 0.10, whereas Ames and Rio Verde had CVs near 0.20. Upon increasing the temperature by 6°, the simulated interannual variability was similar to the baseline for most models in general (Fig. 7). Some models, and at the warmest sites, simulated an increase in the interannual variability with increasing T. Similar observations were made for a + 3 °C increase (data not shown).

Low and high calibration levels – no effect on ensemble response to temperature and CO_2

The modeled ensemble of grain yield response to increased temperature was similar irrespective of the level of information provided for calibration (Fig. 8). The percentage yield decline from 0 °C to +9 °C was −40%, −46%, −62%, and −68% at level L and −36%,
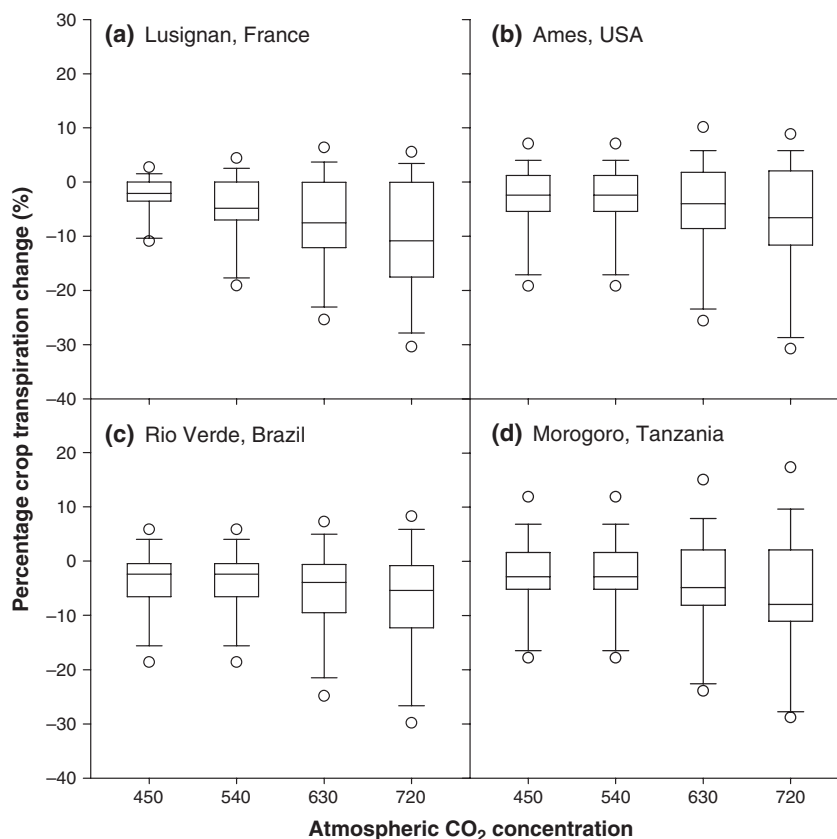
Fig. 6 [CO_2] effect on the percentage change in 30-year average crop transpiration (%) simulated by 15 models at Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d). Box-plot description is similar to Fig. 1 except for the absence of measured and mean values.

−54%, −71%, and −65% at level H, respectively for Lusignan, Ames, Rio Verde, and Morogoro. At each location, the slope of the temperature response did not vary between the L and H information. Neither did the slope vary with location. Finally, the model response to [CO_2] was also not dependent on the level of calibration information (data not shown).

Discussion

By comparing results from a large number of models in four contrasting environments, our work expands the previous efforts (e.g., Eitzinger *et al.* (2013) that only evaluated a 2-week period of drought or elevated temperature after anthesis on maize yield). Our simulations hence explore and define more completely maize crop responses to two major climate change factors (temperature and CO_2) with up to 23 maize simulation models. The effect of rising temperatures on maize yield was strongly negative. The common trend of models simulations to accelerate phenology, especially anthesis in response to temperature, largely explained the main trends for reduction in the other variables studied

(biomass, yield and water use). These simulations were conducted without attempting adaptive measures to ameliorate the impact of higher temperatures, such as changes in planting dates or maize cultivar life cycle duration. Thus, these simulations provide an estimate of the upper boundary of the expected average decrease in maize yield at these locations and under well-watered conditions.

Increased temperature shortened the length of the growing cycle, decreasing opportunity to capture more radiation and reducing total CO_2 assimilation, and reducing total biomass and grain yield as suggested by previous studies (Long, 1991; Guereña *et al.*, 2001; Tao & Zhang, 2011). Therefore, shorter life cycle of current cultivars was a major contributor to reduced grain yield, diminishing leaf area duration and hence, biomass accumulation. Biomass production (data not shown) was affected very similarly to grain yield. On the contrary, the grain harvest index (data not shown) was unaffected by temperature elevation in the 0–6 °C temperature range, except for some reductions at the high (+6 °C or above at Morogoro) or the low temperature extremes (−3 °C in Lusignan and Ames). Raising
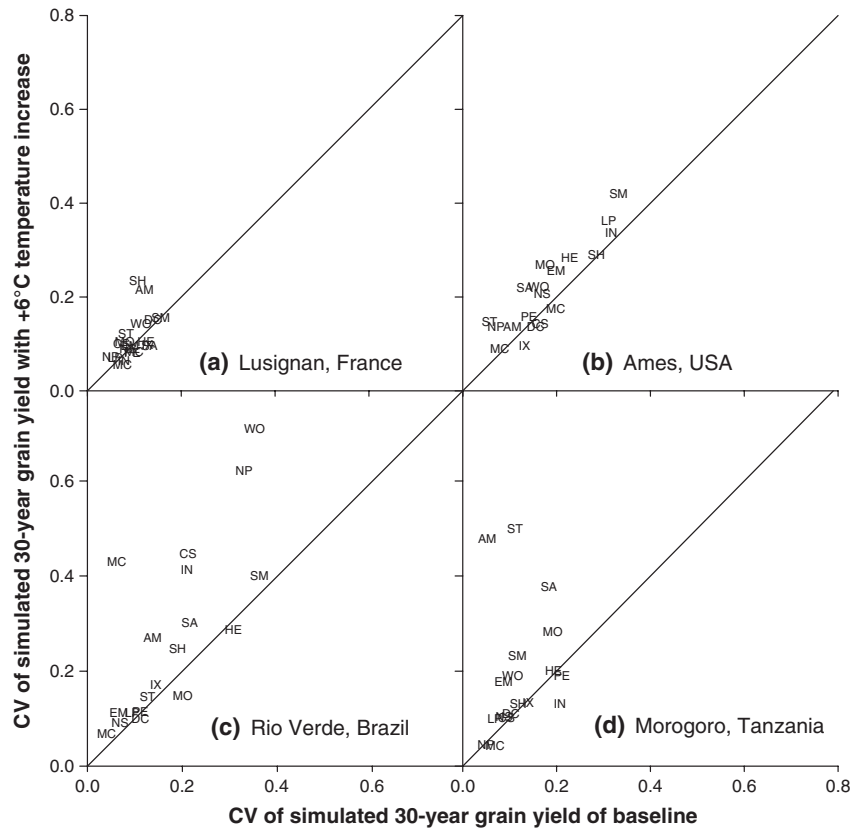
Fig. 7 Interannual coefficient of variation (CV, expressed as fraction) for 30-year simulated grain yield with 6 °C temperature increase vs. CV of 30-year simulated grain yield with baseline using 19 models. Model 2-letter codes are in Table 1. Simulation sites are: Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d).

temperature from −3 to 0 °C indeed caused an increase in yield in the latter cooler locations, due to additional time for grain filling. The growing cycle was not accelerated as much in tropical sites where the average temperature during the growing season was closer to the optimum temperature for maize (Tollenaar *et al.*, 1979). Hybrids with longer cycle (slower developmental rate) may show a lesser reduction in yield as compared with the baseline, and clearly such options for adaptation require systematic evaluation. Also, testing with such an adapted cultivar would answer the question as to what fraction of the yield variation was contributed by life cycle length compared to other direct effects of temperature on assimilation and grain-set (Tao & Zhang, 2010). The relationship between the simulated yield and the average temperature of the growing season suggests that the optimum seasonal temperature is between 22 and 24 °C (across all models), and that grain yield fails (approaches zero) at temperatures near 40 °C (See responses of individual models plotted as a function of the 30-year seasonal temperature in Figure S1 of supplemental materials). Thus, matching the growth cycle to have maximum exposure to the optimum tempera-

ture range while escaping temperatures above 35 °C can be a first initial guide for seeking adaptation to each location.

The variability in simulated yields among the different models at baseline ranged from 4 to 8 Mg ha^{-1}. This range in variation among models in our results increased at higher temperatures across all sites. The increase in simulated yield variability at higher temperatures was due to the higher uncertainty in the maturity date and primary productivity among different models when temperatures increased. Approximately, half of the models simulated LAI using biomass and a specific leaf area while the other half based LAI growth on a morphological leaf-number appearance module depending only on T and stress functions (Table 1). But this did not appear to change the sensitivity to high temperatures, nor did the type of function (vegetative or reproductive) exposed to heat stress.

In C$_4$ species such as maize, the reduction in stomatal conductance with increasing [CO$_2$] brings about an increase in the efficiency of water use with maintenance of CO$_2$ assimilation (Polley, 2002; Long *et al.*, 2006; Tao & Zhang, 2011). In the present study, simulated grain yield responded positively to elevated
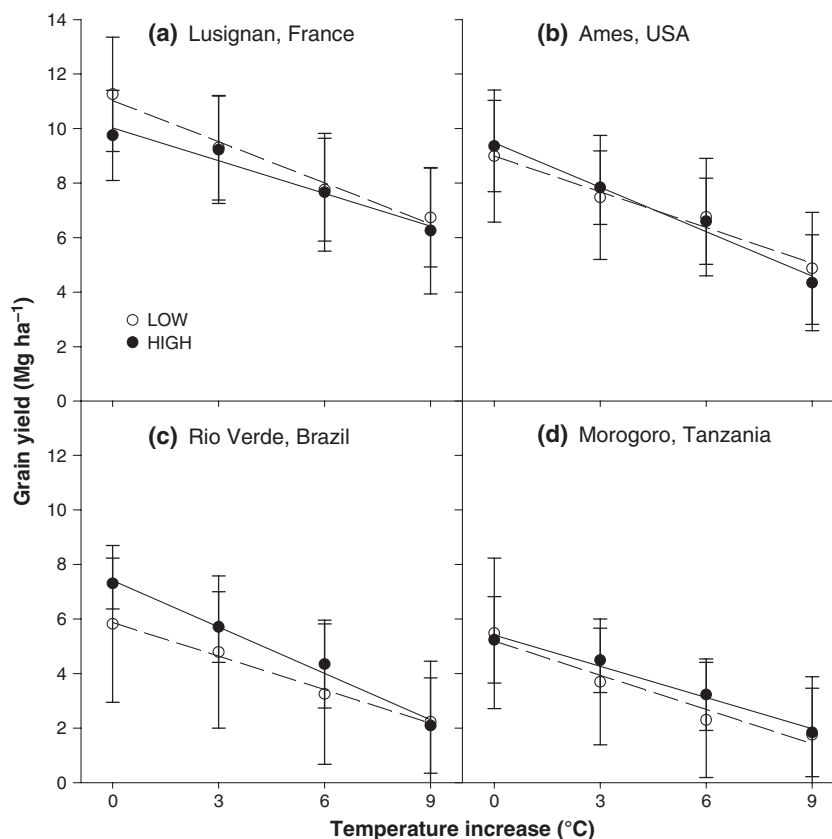
Fig. 8 Simulated effect of temperature increase on median 30-year grain yields (Mg ha^{-1}) obtained with an ensemble of 19 models initially calibrated using low (open points) and high (solid points) level of information at four sites: Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d). Vertical bars represent the standard deviation of the models ensemble median yield simulations. Dashed and continuous lines correspond to the regression of the medians for low and high information levels, respectively. Intercepts and slopes of regression lines were not significantly different.

[CO$_2$] across the 15 models that account for CO$_2$ effects on growth and transpiration, with variations among models. The simulated reduction in crop transpiration was however greater in absolute magnitude than the increase in grain yield. This was expected as photosynthesis of C$_4$ plants is not expected to increase as much as in C$_3$ species under high [CO$_2$] levels (Kimball *et al.*, 2002).

The simulated median percent reduction (8%) in transpiration was less than the 18% reduction reported for maize transpiration with [CO$_2$] increase from 360 to 720 µmol mol^{-1} under well-watered conditions in sunlit controlled environment chambers by Allen *et al.* (2011) and Chun *et al.* (2011). With the exception of a few models, this difference suggests that the studied crop model algorithms for CO$_2$ effect on transpiration may be reducing transpiration insufficiently for C$_4$ species (Boote *et al.*, 2010). A comparison to transpiration of C$_4$ sorghum in the Arizona FACE experiments indicates CO$_2$ effects close to Allen *et al.* (2011) and Chun *et al.* (2011), as a 13% reduction in evapotranspi-

ration was observed with only 200 µmol mol^{-1} increase in [CO$_2$] (Wall *et al.*, 2001; Triggs *et al.*, 2004). Finally, Manderscheid *et al.* (2014) found that in a FACE maize experiment with a similar [CO$_2$] of 550 ppm, crop transpiration was reduced by approximately 0% and 9% in the first and second year, respectively.

The median simulated yield increase with doubled [CO$_2$] was 7.5% across models and four locations, covering a range from 0% yield increase to 19% increase. Indeed, it is noteworthy that this 19% increase was obtained using the Nexpert Spass model, in which photosynthesis was barely different from that of C3 photosynthesis. Furthermore, four models, which explicitly had no response functions to CO$_2$ (N expert-Ceres maize, Sarah, Pegasus and Wofost) were not included in this part of the study, although this absence could be seen as a crop physiological statement of no response. Hence, based on a more inclusive crop physiological selection of models, the ensemble response would have even been lower. This compares to reported maize yield responses to CO$_2$ as low as zero in

free-air CO_2 enrichment (FACE) experiments with 550 μmol mol^{-1} increase (Long *et al.*, 2006; Manderscheid *et al.*, 2014), up to higher values obtained with studies in controlled-environments (27% yield increase at 550 μmol mol^{-1}) (Tubiello *et al.*, 2000; Long *et al.*, 2006). The parameterization of maize models mostly derives from earlier chamber studies that reported a higher C_4 response to CO_2 (Tubiello *et al.*, 2000; Kimball *et al.*, 2002). Uncertainty of C_4 maize response in the literature and resulting uncertainty of C_4 parameterization may account for the high intermodel variability in simulated CO_2 response. These results indicate a need for further studies of the CO_2 effects on canopy photosynthesis and transpiration of C_4 species such as maize. Long *et al.* (2005) proposed that prior experiments are too few and not sufficiently conclusive, and that we need more than theory (Long *et al.*, 2006) suggesting that there are no direct CO_2 effects on C_4 photosynthesis or radiation use.

Interannual variability slightly increased at higher temperatures and it was generally smaller than the intermodel variability. The increase in interannual variability with temperature was especially pronounced in the warmest sites (Fig. 7). Notwithstanding errors arising from extrapolating the simulations outside the conditions where parameters were identified, the interannual variability is likely to increase as temperature rises. Furthermore, the deleterious impacts of extreme temperatures are still poorly taken into account in most models, especially those where growing degree days are computed using simple temperature response functions (e.g., linear) (Eitzinger *et al.*, 2013), so that the increase in variability detected here might be underevaluated.

The yield responses (slopes) of the ensemble of models to temperature and [CO_2] were similar whether the models had been calibrated to sites (high input) or not calibrated to sites (low information input), an aspect that has not been previously explored. The reason for this is that site-specific calibration (heat units to anthesis and maturity, etc.) are separate, mostly cultivar traits. Model relationships such as the cardinal temperatures for phenology, temperature relationships for photosynthesis and seed-growth, and CO_2 response relationships in the code of the models are separate and were unmodified during site-specific calibration.

Moreover, ensemble yields from the multimodels were in good agreement with the trends observed across the four locations when the L level calibration information was used to run the models (Fig. 1), in agreement with the results reported for other cereals (Palosuo *et al.*, 2011; Rötter *et al.*, 2012; Asseng *et al.*, 2013). Our results indicate that with L calibration information, a single model may fail to accurately simulate absolute yield but that an ensemble of models is more likely to approach the correct absolute yield. In all cases, the coefficient of variation exhibited a plateau when n was higher than a given value, that also depended on the site. Fig. 2 suggests that ensembles of 8-10 models would reduce variability substantially. Asseng *et al.* (2013) cited Taylor *et al.* (1999) as an indication that a 13.5% coefficient variation for yield is a fair estimate of variation for field trials over a large regional scale. The number of models needed to reach yield predictions within 13.5% coefficient variation (Fig 2) was 3 at the sites of Lusignan and Ames, 7 in Rio Verde and 13 in Morogoro. It is not surprising that the results obtained in regions where the models had been developed and used, were better simulated than the sites not as well investigated. The better performance of ensemble modeling compared to any single model is remarkable. Some individual models may variously cover or fail to address or incorrectly address certain field-important aspects, but others do. Examples would include: direct heat-stress effects on grain-set, stressfully high temperatures on photosynthesis, stressful temperatures on grain-growth rate, and life cycle under elevated temperature (most models accelerate too much). By putting the models together, some of the better features of individual models may act to offset the failures of correct inclusion of a process in other models. Similarly, variation among individual models in structure (equations) and parameter values also contribute to the observed variations. Hence, the better precision of the ensemble may result from a statistical sampling of possible models (and aggregation over multiple samples) just as more replicates play a role in better experimental assessment of a local variable (yield, rainfall, etc.). Taking more samples of possible maize models improves the average response over taking a single model, since we don't know which maize model is correct at a given site. An aggregated yield average over many samples (of models) is better than a value coming from one sample.

Our study does not in any way attempt to compute a projection of maize yields under future climate change. However, given the noticeable agreement between simulations, these responses to rising temperatures indicate that the rising temperature aspect of climate change could be a significant challenge for local food production if adaptive management cannot reduce the predicted yield losses of 4–7% per degree of local warming, with some regions potentially experiencing even more dramatic declines if no adjustment can be made. Even a conservative target of 2 °C global mean warming would imply a reduction of 8–14% in global maize production with only a modest beneficial effect of enhanced [CO_2] on the C_4 crop. Will the increase in

CO_2 actually have such a limited positive impact as simulated in this study? Above all, effective mitigation of climate change is thus important to maintain agricultural production, especially in places where water is expected to be even less available in the future. However, given the range of durations of growing cycles (flowering and maturity) in the already available cultivars, adaptation also could be useful for sustaining maize production in impacted regions. Crop models need to be applied also to explore suitable measures of adaptation, such as slower maturing cultivars, heat tolerant cultivars, as well as drought tolerant cultivars. Furthermore, unknown areas of high-latitude regions currently unable to produce maize crops due to low temperatures may become productive.

Acknowledgements

References

Adams RM, Rosenzweig C, Peart RM et al. (1990) Global climate change and US agriculture. Nature, 345, 219–224.

Adams RM, Hurd BH, Lenhart S, Leary N (1998) Effects of global climate change on agriculture: an interpretative review. Climate Research, 11, 19–30.

Aggarwal PK, Kalra N, Chander S, Pathak H (2006) InfoCrop: a dynamic simulation model for the assessment of crop yields losses due to pests and environmental impact of agro-ecosystems in tropical environments I. Model Description Agricultural Systems, 89, 1–25.

Allen LH Jr, Kakani VG, Vu JCV, Boote KJ (2011) Elevated CO_2 increases water use efficiency by sustaining photosynthesis of water-limited maize and sorghum. Journal of Plant Physiology, 168, 1909–1918.

Angulo C, Rötter R, Trnka M, Pirttioja N, Gaiser T, Hlavinka P, Ewert F (2013) Characteristic 'fingerprints' of crop model responses to weather input data at different spatial resolutions. European Journal of Agronomy, 49, 104–114.

Asseng S, Ewert F, Rosenzweig C et al. (2013) Uncertainties in simulating wheat yields under climate change. Nature Climate Change, 3, 827–832.

Baron C, Sultan B, Balme M et al. (2005) From GCM grid cell to agricultural plot: scale issues affecting modelling of climate impact. Philosophical transactions of the royal society of London. Biological Sciences, 360, 2095–2108.

Basso B, Cammarano D, Troccoli A, Chen D, Ritchie JT (2010) Long-term wheat response to nitrogen in a rainfed Mediterranean environment: field data and simulation analysis. European Journal of Agronomy, 33, 132–138.

Bondeau A, Smith PC, Zaehle S et al. (2007) Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology, 13, 679–706.

Boogaard HL, Van Diepen CA, Roetter RP, Cabrera JMCA, Laar HHv (1998) WOFOST 7.1: user's guide for the WOFOST 7.1 crop growth simulation model and WOFOST Control Center 1.5. Technical document/DLO Winand Staring Centre;52. DLO Winand Staring Centre, Wageningen.

Boote KJ, Allen LH Jr, Prasad PVV, Jones JW (2010) Testing effects of climate change in crop models. In: Handbook of Climate Change and Agroecosystems (eds Hillel D, Rosenzweig C), pp. 109–129. Imperial College Press, London UK.

Boote KJ, Amir MHI, Lafitte R et al. (2011) Position statement on crop adaptation to climate change. Crop Science, 51, 2337–2343.

Brisson N, Ruget F, Gate P et al. (2002) – STICS: a generic model for the simulation of crops and their water and nitrogen balances. II- Model validation for wheat and maize. Agronomie, 22, 69–92.

Brisson N, Gary C, Justes E et al. (2003) An overview of the crop model STICS. European Journal of Agronomy, 18, 309–332.

Bruinsma J (2009) The Resource Outlook to 2050. By How Much do Land, Water and Crop Yields Need to Increase by 2050? FAO Expert Meeting on How to Feed the World in 2050. FAO, Rome.

Chun JA, Wang Q, Timlin D, Fleisher D, Reddy VR (2011) Effect of elevated carbon dioxide and water stress on gas exchange and water use efficiency in corn. Agricultural and Forest Meteorology, 151, 378–384.

Deryng D, Sacks WJ, Barford CC, Ramankutty N (2011) Simulating the effects of climate and agricultural management practices on global crop yield. Global Biogeochemical Cycles, 25, 1–18.

Diekkrüger B, Söndgerath D, Kersebaum KC, McVoy CW (1995) Validity of agroecosystem models – a comparison of results of different models applied to the same data set. Ecological Modelling, 81, 3–29.

Eitzinger J, Thaler S, Schmid E et al. (2013) Sensitivities of crop models to extreme weather conditions during flowering period demonstrated for maize and winter wheat in Austria. Journal of Agricultural Science, 151, 813–835.

Ewert F, Angulo C, Rumbaur C et al. (2011) Scenario development and assessment of the potential impacts of climate and market changes on crops in Europe. Agri-Adapt project reports, no. 2 & 3, July 2011. 49 pp.

FAO (2012) FAO Statistical Year Book (2012) Europe and Central Asia. Food and Agriculture. FAO, Roma. www.FAO.org (accessed 27 January 2014).

Farquhar GD, von Caemmerer S, Berry JA (1980) A biochemical model of photosynthetic CO_2 assimilation in leaves of C_3 species. Planta, 149, 78–90.

Goudriaan J (1996) Predicting crop yields under global change. In: Global Change and Terrestrial Ecosystems, (eds Walker BH, Steffen W), pp. 260–274. Cambridge University Press, New York.

Guereña A, Ruiz-Ramos M, Díaz-Ambrona CH, Conde JR, Inés Mínguez M (2001) Assessment of climate and agriculture in Spain using climate models. Agronomy Journal, 93, 237–249.

Jing Q, Conijn SJG, Jongschaap REE, Bindraban PS (2012) Modeling the productivity of energy crops in different agro-ecological environments. Biomass and Bioenergy, 46, 618–633.

Jones CA, Kiniry JR (1986) CERES-Maize: A Simulation Model of Maize Growth and Development. Texas A&M Univ. Press, College Station.

Jongschaap REE (2007) Sensitivity of a crop growth simulation model to variation in LAI and canopy nitrogen used for run-time calibration. Ecological Modelling, 200, 89–98.

Kanai R, Edwards GE (1973) Separation of mesophyll protoplasts and bundle sheath cells from maize leaves for photosynthetic studies. Plant Physiology, 51, 1133–1137.

Keating BA, Carberry PS, Hammer GL et al. (2003) An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy, 18, 267–288.

Kersebaum KC (2007) Modelling nitrogen dynamics in soil–crop systems with HERMES. Nutrient Cycling in Agroecosystems, 77, 39–52.

Kersebaum KC, Nendel C (2014) Site-specific impacts of climate change on wheat production across regions of Germany using different CO_2 response functions. European Journal of Agronomy, 52, 22–32.

Kim S-H, Yang Y, Timlin DJ, Fleisher DH, Dathe A, Reddy VR, Staver K (2012) Modeling temperature responses of leaf growth, development, and biomass in maize with MAIZSIM. Agronomy Journal, 104, 1523–1537.

Kimball BA, Kobayashi K, Bindi M (2002) Responses of agricultural crops to free-air CO_2 enrichment. Advances in Agronomy, 77, 293–368.

Lizaso JI, Boote KJ, Jones JW, Porter CH, Echarte L, Westgate ME, Sonohat G (2011) CSM-IXIM: a new maize simulation model for DSSAT v4.5. Agronomy Journal, 103, 766–779.

Long SP (1991) Modification of the response of photosynthetic productivity to rising temperature by atmospheric CO_2 concentrations: has its importance been underestimated? Plant, Cell & Environment, 14, 729–739.

Long SP, Ainsworth EA, Leakey ADB, Morgan PB (2005) Global food insecurity. Treatment of major food crops with elevated carbon dioxide and ozone under large-scale fully open-air conditions suggests models may seriously over-estimate future yields. Philosophical Transactions of the Royal Society B, 360, 2011–2020.

Long SP, Ainsworth EA, Leakey ADB, Nosberger J, Ort DR (2006) Food for thought: lower than expected crop yield stimulation with rising CO_2 concentrations. Science, 312, 1918–1921.

Maltas A, Corbeels M, Scopel E, Oliver R, Douzet JM, Macena da Silva FA, Wery J (2007) Long-term effects of continuous direct seeding mulch-based cropping systems on soil nitrogen supply in the Cerrado region of Brazil. Plant and Soil, 298, 161–173.

Maltas A, Corbeels M, Scopel E, Wery J, Macena da Silva FA (2009) Cover crop and nitrogen effects on maize productivity in no-tillage systems of the Brazilian cerrados. Agronomy Journal, 101, 1036–1046.

Manderscheid R, Erbs M, Weigel HJ (2014) Interactive effects of free-air CO_2 enrichment and drought stress on maize growth. *European Journal of Agronomy*, **52**, 11–21.

McMaster GS, Wilhelm WW (1997) Growing degree-days: one equation, two interpretations. *Agricultural and Forest Meteorology*, **87**, 291–300.

Monteith JL (1977) Climate and the efficiency of crop production in Britain. *Philosophical Transactions of the Royal Society B*, **281**, 277–294.

Muchow RC, Sinclair TR, Bennett JM (1990) Temperature and solar radiation effects on potential maize yield across locations. *Agronomy Journal*, **82**, 338–343.

Nendel C, Berg M, Kersebaum KC *et al.* (2011) The MONICA model: testing predictability for crop growth, soil moisture and nitrogen dynamics. *Ecological Modelling*, **222**, 1614–1625.

Palosuo T, Kersebaum KC, Angulo C *et al.* (2011) Simulation of winter wheat yield and its variability in different climates of Europe. A comparison of eight crop growth models. *European Journal of Agronomy*, **35**, 103–114.

Polley HW (2002) Implications of atmospheric and climatic change for crop yield and water use efficiency. *Crop Science*, **42**, 131–140.

Porter JR, Semenov MA (2005) Crop responses to climatic variability. *Philosophical Transactions of the Royal Society B*, **360**, 2021–2035.

Rienecker MR, Suarez MJ, Gelaro R *et al.* (2011) MERRA - NASA's modern-era retrospective analysis for research and applications. *Journal of Climate*, **24**, 3624–3648.

Rosenzweig C, Wilbanks TJ (2010) The state of climate change vulnerability, impacts, and adaptation research: strengthening knowledge base and community. *Climatic Change*, **100**, 103–106.

Rosenzweig C, Jones JW, Hatfield JL *et al.* (2013) The agricultural model intercomparison and improvement project: protocols and pilot studies. *Agricultural and Forest Meteorology*, **170**, 166–172.

Rötter RP, Timothy RC, Jørgen EO, Porter JR (2011) Crop-climate models need an overhaul. *Nature Climate Change*, **1**, 175–177.

Rötter RP, Palosuo T, Kersebaum KC *et al.* (2012) Simulation of spring barley yield in different climatic zones of Northern and Central Europe. A comparison of nine crop models. *Field Crops Research*, **133**, 23–36.

Singh P, Boote KJ, Kumar U, Srinivas K, Nigam SN, Jones JW (2012) Evaluation of genetic traits for improving productivity and adaptation of groundnut to climate change in India. *Journal of Agriculture and Crop Sciences*, **198**, 399–413.

Stenger R, Priesack E, Barkle G, Sperr C (1999) Expert-N, a tool for simulating nitrogen and carbon dynamics in the soil-plant-atmosphere system. In: *NZ land treatment collective, Proceedings of technical session 20: modelling of land treatment systems*, (eds. Tomer M, Robinson M and Gielen G), pp. 19–28.

Stöckle CO, Dyke PT, Williams JR, Jones CA, Rosenberg NJ (1992) A method for estimating the direct and climatic effects of rising atmospheric carbon dioxide on growth and yield of crops: part II-sensitivity analysis at three sites in the midwestern USA. *Agricultural Systems*, **38**, 239–256.

Stöckle CO, Donatelli M, Nelson R (2003) CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, **18**, 289–307.

Tanner CB (1981) Transpiration efficiency of potato. *Agronomy Journal*, **73**, 59–64.

Tao F, Zhang Z (2010) Adaptation of maize production to climate change in north China plain: quantify the relative contributions of adaptation options. *European Journal of Agronomy*, **33**, 103–116.

Tao F, Zhang Z (2011) Impacts of climate change as a function of global mean temperature: maize productivity and water use in China. *Climatic Change*, **105**, 409–432.

Tao F, Yokozawa M, Zhang Z (2009a) Modelling the impacts of weather and climate variability on crop productivity over a large area: a new process-based model development, optimization, and uncertainties analysis. *Agricultural and Forest Meteorology*, **149**, 831–850.

Tao F, Zhang Z, Liu J, Yokozawa M (2009b) Modeling the impacts of weather and climate variability on crop productivity over a large area: a new super-ensemble-based probabilistic projection. *Agricultural and Forest Meteorology*, **149**, 1266–1278.

Taylor SL, Payton ME, Raun WR (1999) Relationship between mean yield, coefficient of variation, mean square error and plot size in wheat field experiment. *Communications in Soil Science and Plant Analysis*, **30**, 1439–1447.

Tayot X, Ruget F, Bouthier A, Lorgeou J, Lacroix B, Pons Y (1999) Stics en Poitou-Charentes. Calibration et validation sur maïs et sorgho. *Perspectives Agricoles*, **242**, 86–95.

Tollenaar M, Daynard TB, Hunter RB (1979) Effect of temperature and rate of leaf appearance and flowering date in maize. *Crop Science*, **19**, 363–366.

Triggs JM, Kimball BA, Pinter PJ Jr *et al.* (2004) Free-air carbon dioxide enrichment (FACE) effects on energy balance and evapotranspiration of sorghum. *Agricultural and Forest Meteorology*, **124**, 63–79.

Tubiello F, Ewert F (2002) Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. *European Journal of Agronomy*, **18**, 57–74.

Tubiello FN, Donatelli M, Rosenzweig C, Stöckle CO (2000) Effects of climate change and elevated CO_2 on cropping systems: model predictions at two Italian locations. *European Journal of Agronomy*, **13**, 179–189.

Von Caemmerer S (2000) *Biochemical Models of Leaf Photosynthesis*. CSIRO Publishing, Collingwood, Australia.

Wall GW, Brooks TJ, Adam R *et al.* (2001) Elevated atmospheric CO_2 improved sorghum plant water status by ameliorating the adverse effects of drought. *New Phytologist*, **152**, 231–248.

White JW, Hoogenboom G, Kimball BA, Wall GW (2011) Methodologies for simulating impact of climate change on crop production. *Field Crops Research*, **124**, 357–368.

Williams JR, Jones CA, Kiniry JR, Spanel DA (1989) The EPIC crop growth model. *Transactions of the ASAE*, **32**, e511.

Yang HS, Dobermann A, Cassman KG, Lindquist JL, Walters DT, Arkebauer TJ, Cassman KG (2004) Hybrid-Maize: a maize simulation model that combines two crop modelling approaches. *Field Crops Research*, **87**, 131–154.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. The simulated 30-year mean grain yield (Mg ha^{-1}) of the individual models as a function of the 30-year seasonal temperature of the simulated growing seasons at Lusignan, France (circle, mean baseline temperature 17 °C) (a), Ames, USA (triangle, mean baseline temperature 21 °C) (b), Rio Verde, Brazil (diamond, mean baseline temperature 25 °C) (c), Morogoro, Tanzania (square, mean baseline temperature 27 °C) (d).

Figure S2. The simulated 30-year grain yield (Mg ha^{-1}) response of individual models to temperature increase at Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d). Mean baseline temperatures during the growing cycle were 17, 21, 25 and 27 °C in Lusignan, Ames, Rio Verde and Morogoro, respectively.

Figure S3. Temperature effect on 30-year phenology (days after sowing to reach anthesis, DAS) simulated by the individual models at Lusignan (France), Ames (USA), Rio Verde (Brazil), and Morogoro (Tanzania). Mean baseline temperatures during the growing cycle were 17, 21, 25 and 27 °C in Lusignan, Ames, Rio Verde and Morogoro, respectively. When a model could not simulate maturity at high or low temperature, the line is interrupted (MC, in Rio Verde and Morogoro).

Figure S4. Temperature effect on 30-year phenology (days after sowing to reach maturity, DAS) simulated by the individual models at Lusignan (France), Ames (USA), Rio Verde (Brazil), and Morogoro (Tanzania). Mean baseline temperatures during the growing cycle were 17, 21, 25 and 27 °C in Lusignan, Ames, Rio Verde and Morogoro, respectively.

Figure S5. CO_2 effect on 30-year percentage response in grain yield (%) simulated by the individual models at Lusignan, France (a), Ames, USA (b), Rio Verde, Brazil (c), Morogoro, Tanzania (d).

Figure S6. Individual model simulations of the response of crop transpiration (% average of 30 years baseline) to [CO_2] (μmol mol^{-1}) in the four sites studied.